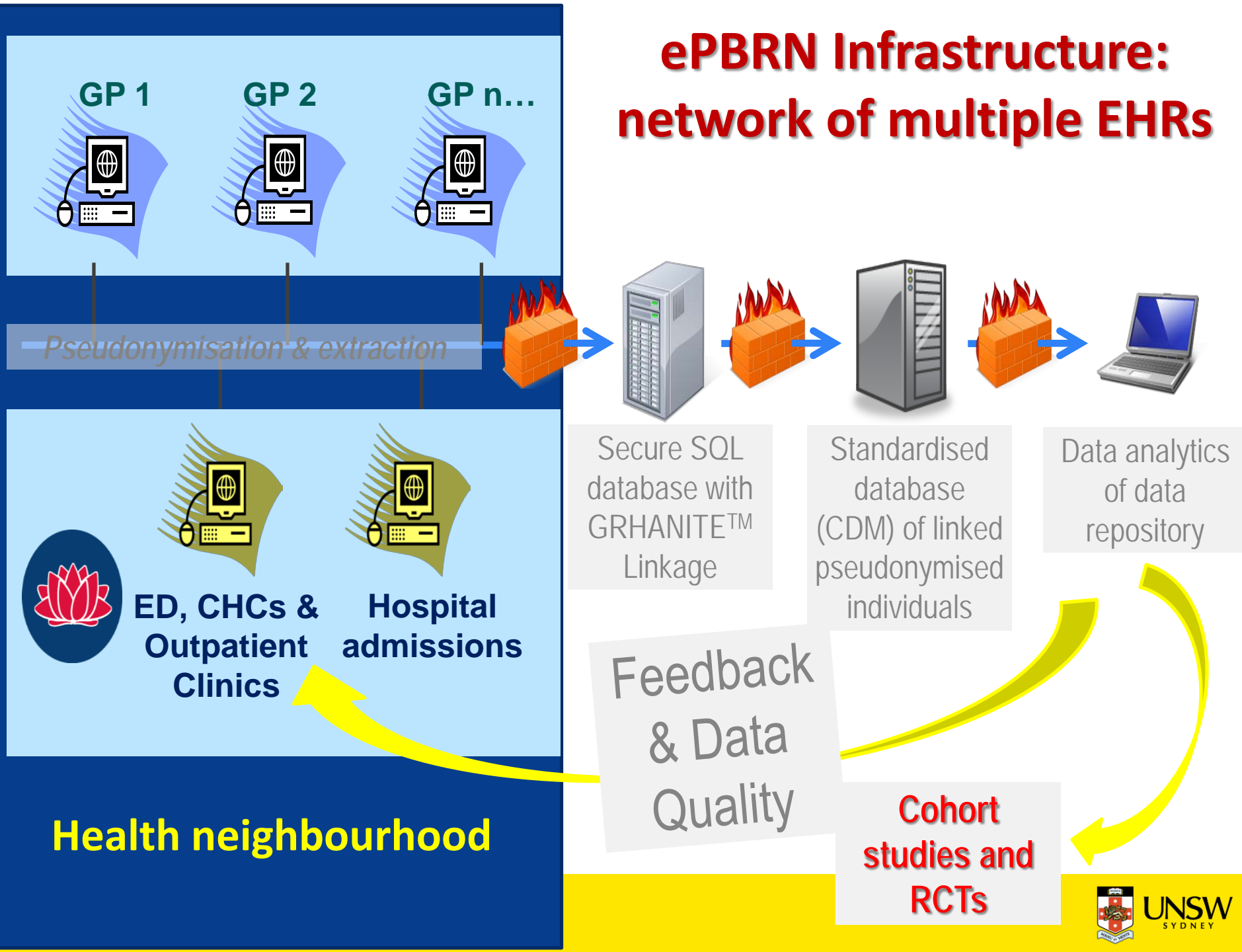




UNSW ePBRN & OMOP-CDM

ePBRN Infrastructure: network of multiple EHRs



Digital health to connect actors

1. Readiness to connect

Capability maturity/enablers

Infrastructure : EHR & ePBRN

2. Connect data, systems, tools:

Common Data Model

Data linkage, cohorts, continuity of care

3. Connect services & practitioners:

Acute-primary care continuum

Chronic disease/cancer mx

teleHealth & mHealth: apps

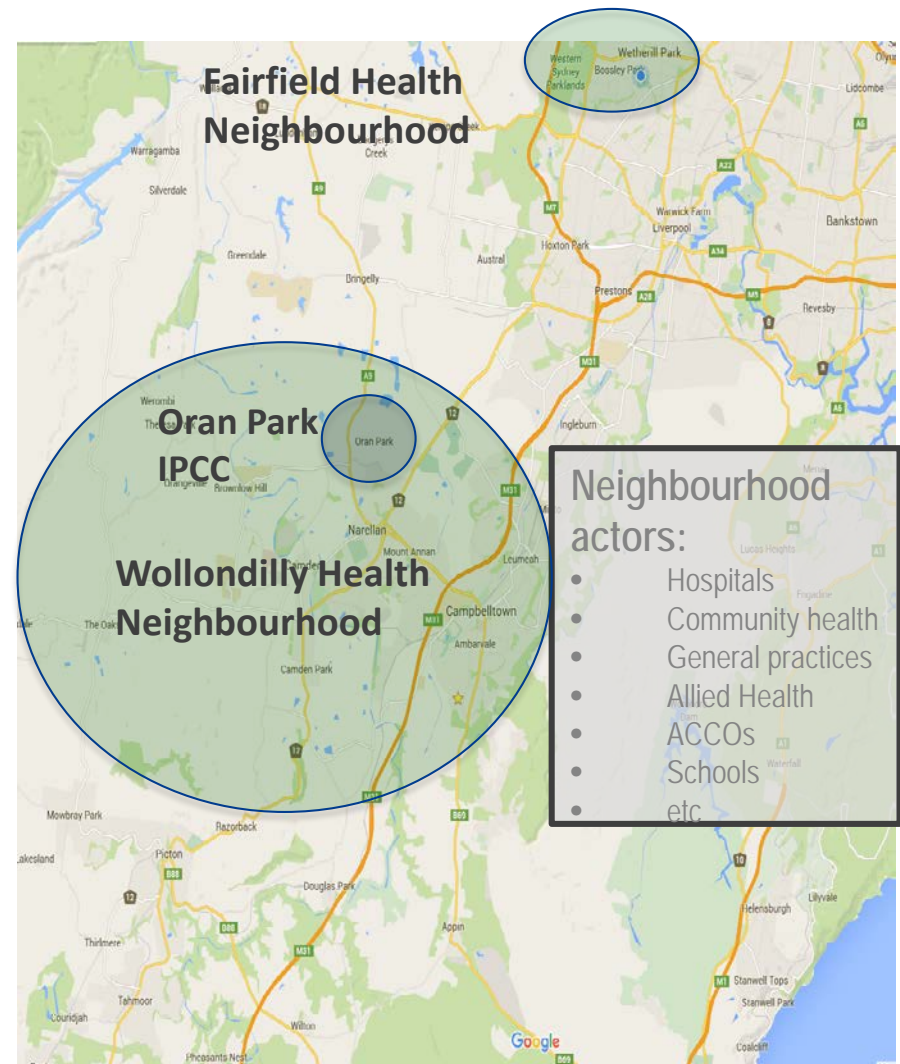
4. Connect citizens & community:

Equitable access: IMPACT, HeLP

Health Alliances

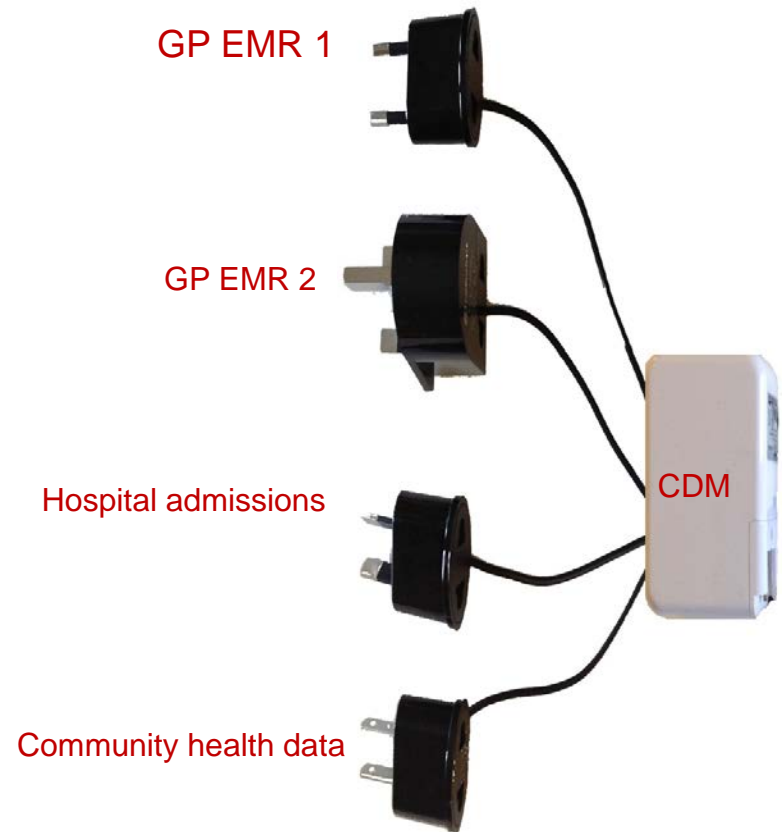
Schools: Ashcroft school nurse

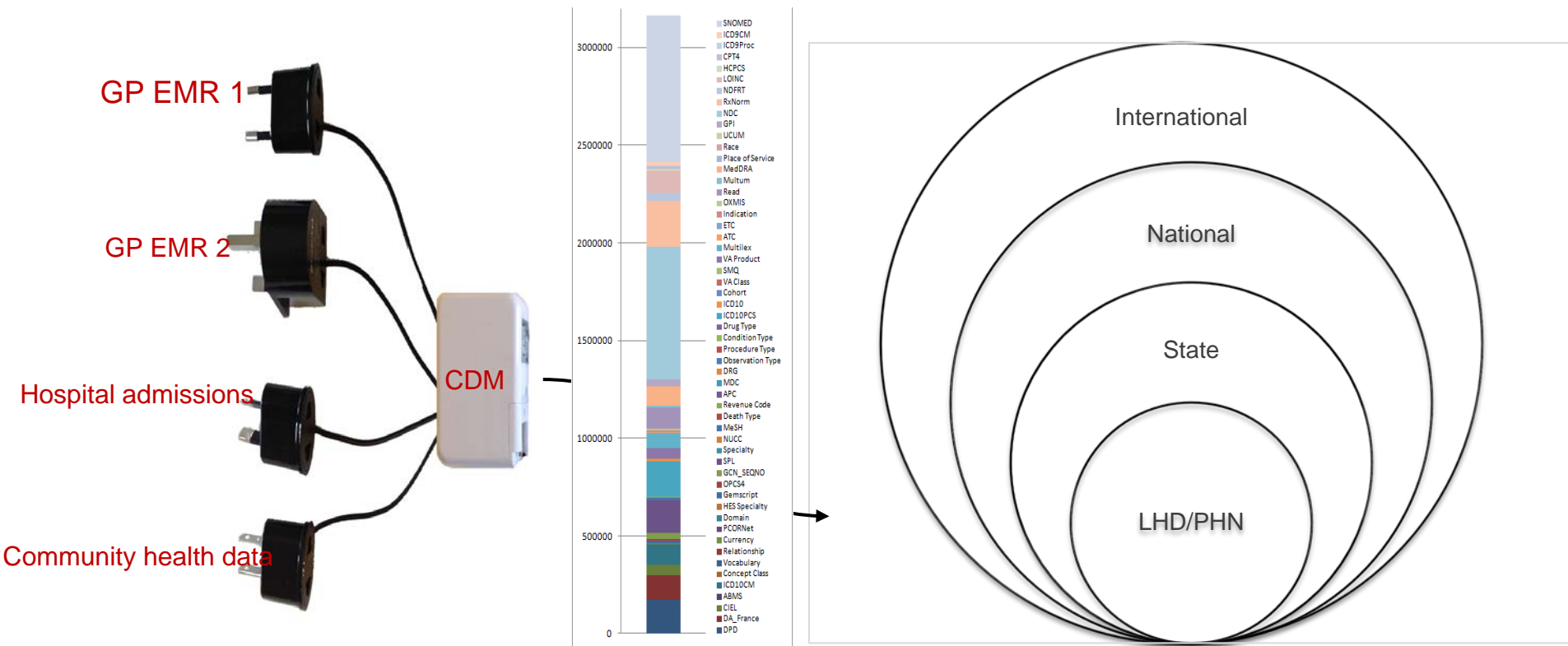
Culturally and clinically appropriate care
(WoTWoD)



The curse of interoperability

- Undertaking large scale analysis across multiple sites requires dealing with heterogenous data sources
- Often different types of standard vocabularies used in each source system

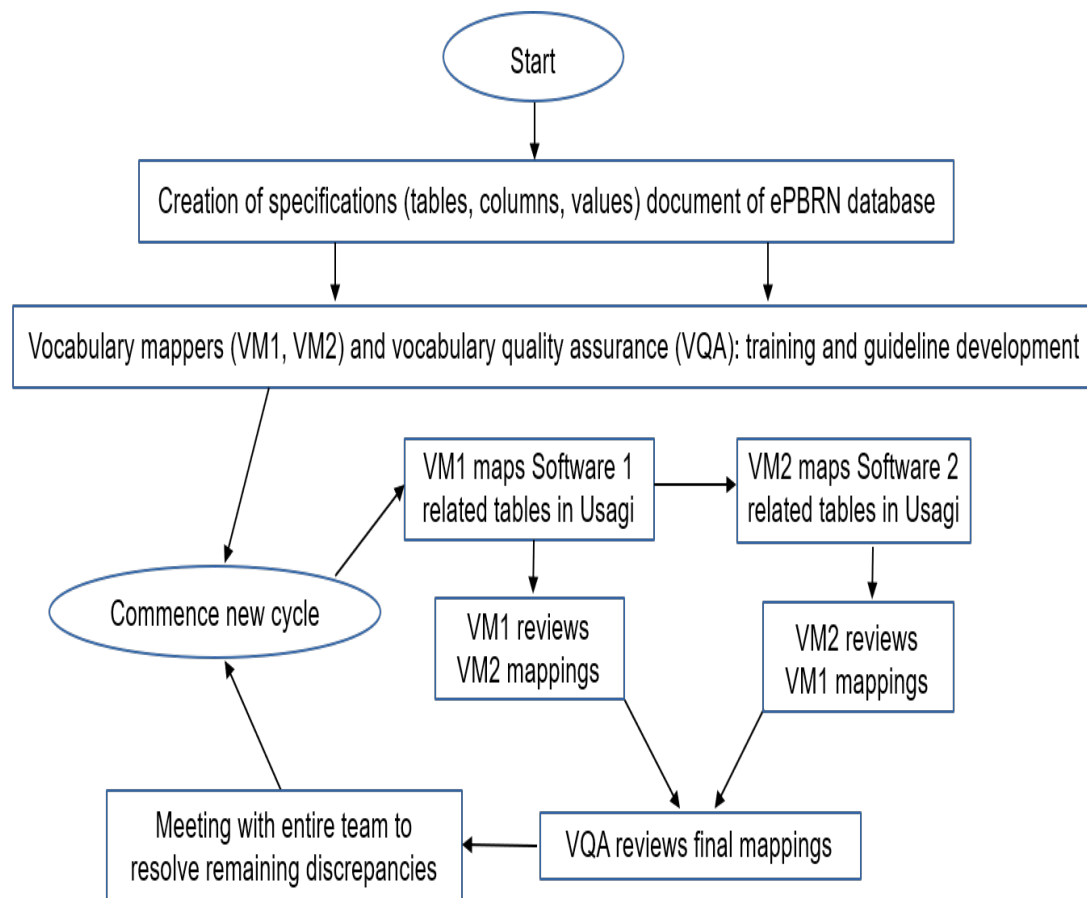




Observational medical outcomes research

OMOP-CDM Vocabulary mapping

- Adopted an iterative approach involving all the team members
- Medical students recruited as mappers
- Mappings are reviewed by the research assistant



Challenges

- Limited coverage of Australian terminologies/concepts
- Vocabulary mapping is very tedious
 - Especially when the source EMRs don't use standardized vocabularies. MedicalDirector EMR uses DOCLE
 - and subjective, example below
- The standards can be still subjective with out appropriate conventions in place. For example, how to handle duplicate diagnoses ? What if data is not available in mandatory fields ?
- Harmonizing observational EHR data is more complex than harmonizing registry or claims data.
- CDM doesn't cover many complex aspects observed with secondary usage of EHR data. **For example, storing linkage information**
- How do we validate the data quality after the ETL process into OMOP-CDM?

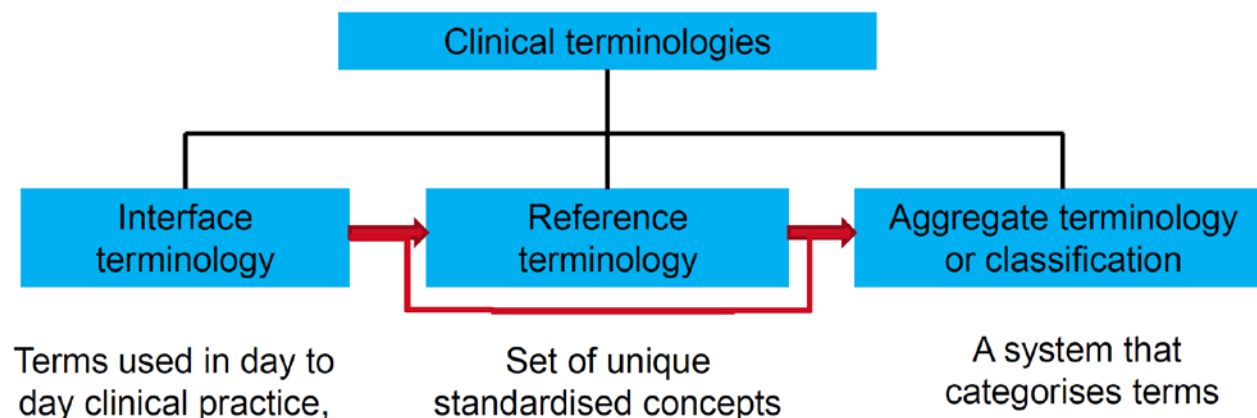
Comparison of AMT-ATC mapping in cohort selection

Background & objectives

- AMT is a reference terminology which describes each drug available in Australia.
- ATC is a classification that aims to group drugs based on their properties.
- Classifications provides efficient methods to easily include or exclude groups of patients. It can be used for cohort selection in observational studies or RCT.
- Effectiveness in cohort selection dependent on data quality and mapping accuracy
- Explore the existing mappings from two sources – **PBS** and **OMOP-CDM**
 - Identify which mapping performs better for cohort identification.

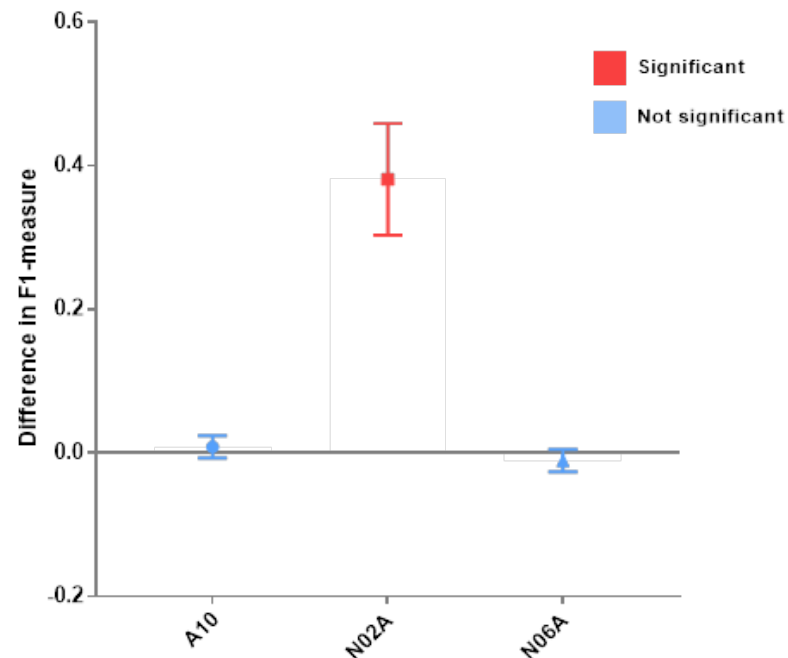
AMT = Australian Medicines Terminology

ATC = Anatomical, Therapeutic & Chemical classification



Result summary

ATC Group	OMOP Mappings	PBS Mappings	Difference
A10	82	84	2 (2.4%)
N02A	62	141	79 (101%)
N06A	115	112	3 (2.6%)



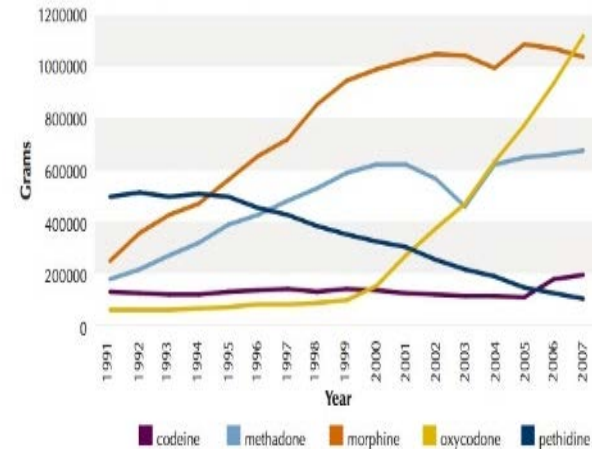
ATC Group	OMOP-CDM Mapping			PBS Mapping			ATC Groups		
	Recal	Precision	F-measure	Recall	Precision	F-measure	Difference in F-measure	95% CI	P-value
A10 (Drugs used in diabetes)	0.943	1	0.970	0.966	1	0.982	0.012	-0.00693, 0.0241	0.234
N02A (Opioids)	0.389	1	0.561	0.887	1	0.940	0.379	0.299, 0.450	< 0.0001
N06A (Antidepressants)	1	1	1	0.974	1	0.987	0.013	-0.0264, 0.00496	0.127

Use and misuse of opioids in general practice using observational EHR data

Assessing the use of opioids using EHR

- Opioids were initially developed for the treatment of malignancy-related pain but there was a push for its use to treat chronic nociceptive and neuropathic pain in 1995.
- Between 1990-2014, there has been a four-fold increase in pharmaceutical opioid (PO) use in Australia and correspondingly, marked increases in rates of PO-related deaths, mostly by accidental overdose.
- A group at high risk of opioid-related harm are doctor shoppers as they have twice the risk of drug-related mortality and opioid-related hospital admissions.

Figure 4: Pharmaceutical opioid base supply (grams) Australia from 1991-2007



Source: Dobbin 2008, Morphine, Unpublished paper provided to the Drugs and Crime Prevention Committee. Data extracted from the National Drug-control System (NDS) domestic transaction data by the Commonwealth Department of Health and Ageing.



Of opioid deaths in 2016:

- **550** mentioned **other opioids** (includes prescription painkillers such as oxycodone, morphine and codeine)
- **361** mentioned **heroin**
- **208** mentioned **methadone**
- **234** mentioned **other synthetic narcotics** (for example, fentanyl and tramadol).

Study Aim

To use linked routinely collected primary care and general practice data to identify a cohort of opioid users to answer the following research questions:

1. *Is EHR a viable source for investigating opioid usage in primary care?*
2. *Identify the risk factors such as age, gender, co-morbidities of opioid use.*
3. *Does the continuity of care measured in Usual Provider of Care (UPC)¹⁶ affect the amount of opioid use?*

Methodology

- UNSW electronic practice-based research network (ePBRN)
- Opioids included are oral, sublingual and transdermal formulations of those under the Anatomical Therapeutically Chemical (ATC) classification drug code category *NO2A* (opioids) and *NO7BC* (drugs used in opioid dependence).
- Drug amounts converted to oral morphine equivalent dose (oMED) to represent opioid use at the population level instead of Defined Daily Doses (DDD)

Variables	Details
Type of opioid	Codeine, Hydromorphone, Morphine, Oxycodone, Oxycodone+Naloxone, Fentanyl, Methadone, Buprenorphine, Aspirin+codeine, Paracetamol+Codeine, Tapentadol, Tramadol
Prescription Reason	The reason for the prescription.
Drug Usage	Drug usage in oral morphine equivalent dose
Date of prescription	Date of prescription
Prescribed dose of drug	Prescribed dose of drug (mg)
Prescription period	First to last date of prescription by one prescriber for shared patients only

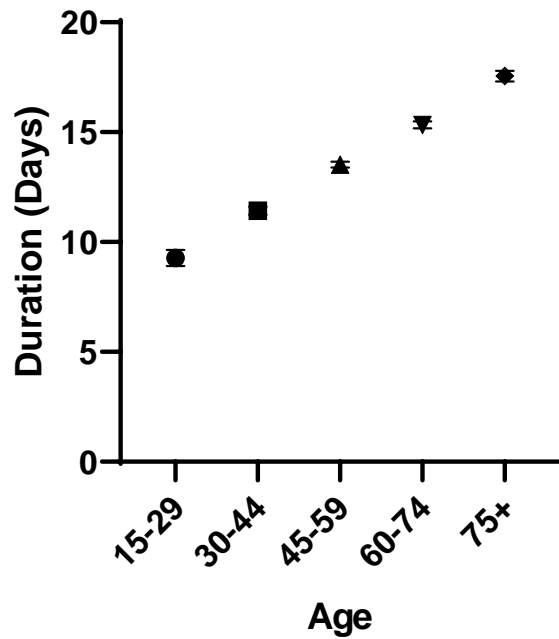
Results

	Category	Mean (SD) / Count (Percentage)
Age		52.61 (18.01)
Sex:	Male	5920 (53.6%)
	Female	6848 (46.3%)
	No Information / Other	10 (0.1%)
Alcohol Status:	Drinker	2418 (18.9%)
	Non-Drinker	30 (0.2%)
	No information	10330 (80.8%)
Smoking Status:	Smoker	2575 (20.2%)
	Non-Smoker	5781 (45.2%)
	Ex-Smoker	2490 (19.5%)
	No information	1932 (15.1%)
Conditions:	Neuropathic pain	467 (3.7%)
	Cancer related pain	672 (5.3%)
Shared patients across practices	2	236 (1.8%)
	3	10 (0.1%)

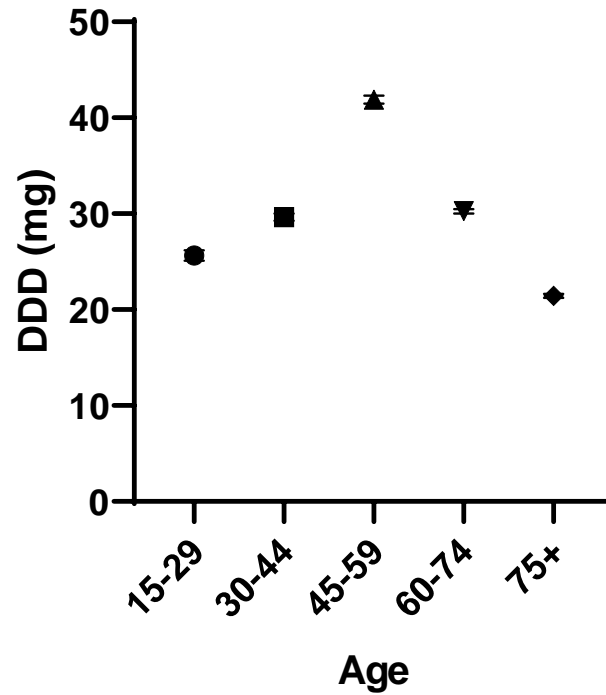
Mental illness co-morbidities:	Anxiety	1726 (13.5%)
	Depression	2252 (17.6%)
	Schizophrenia	81 (0.6%)
Number of mental illness co-morbidities	1	2280 (17.8%)
	2	869 (6.8%)
	3	13 (0.1%)
	≥ 1	3163 (24.8%)

Results

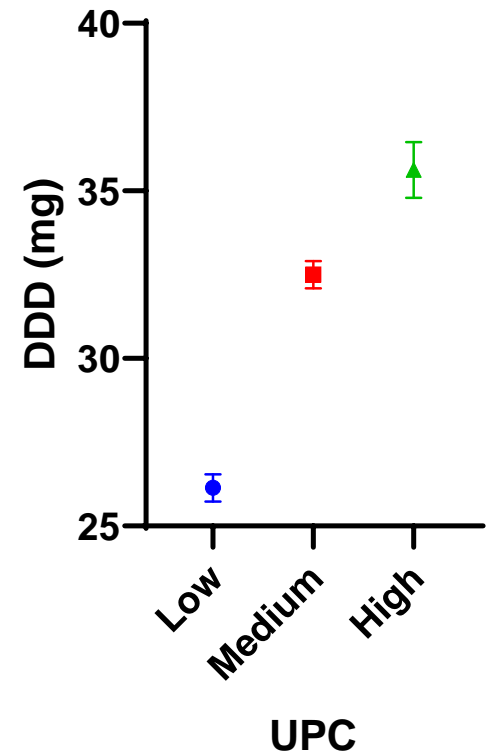
Duration Vs age group

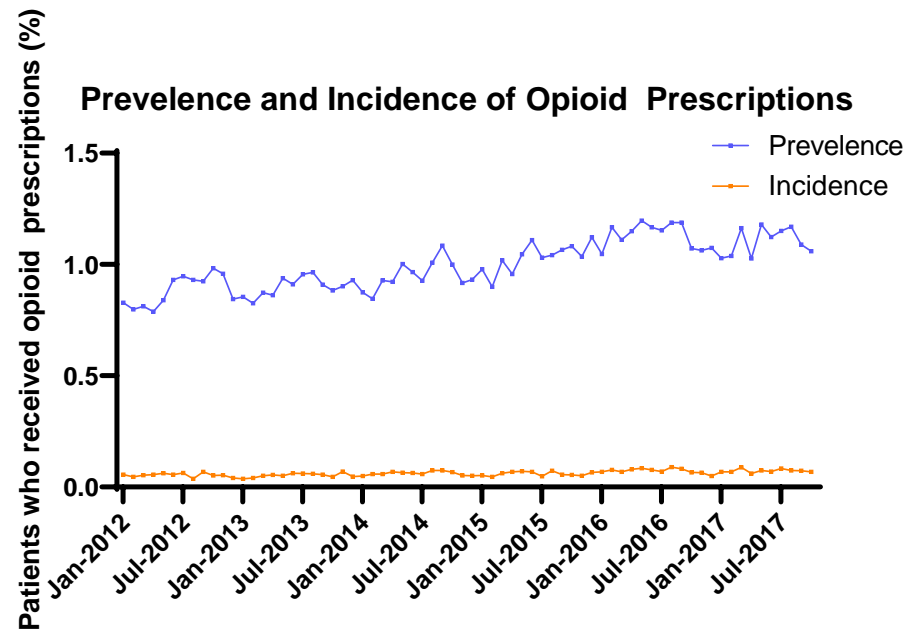
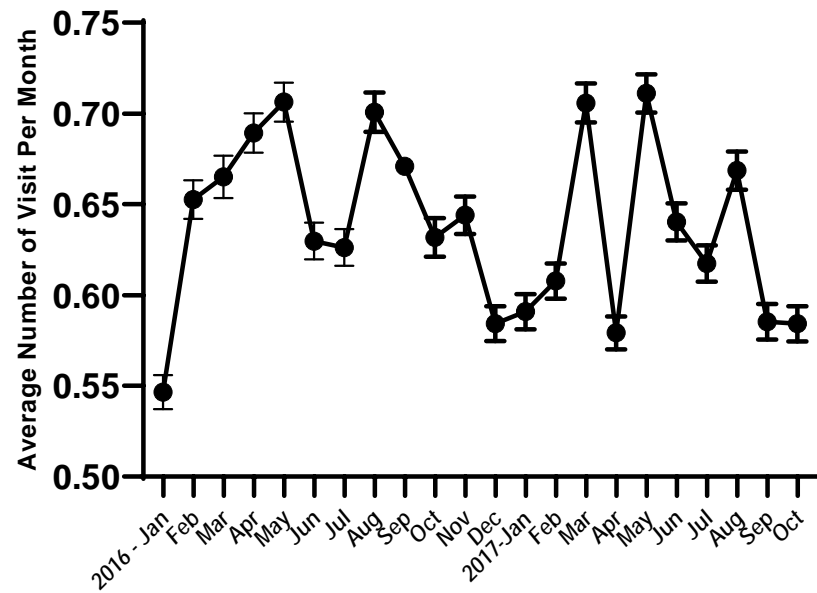


DDD vs Age group



DDD vs UPC





Other On-going projects

- Monitoring quality of care using continuity of care
- Machine learning based patient record linkage
- ETL Validation on Data quality

FUTURE: ePBRN

Infrastructure: Internet of Things

GP n...



Apps



Wearables



Pseudonymisation & ETL



Secure SQL
database with
GRHANITE™
Linkage

Standardised
database
(CDM) of
linked
pseudonymise
d individuals

Data analytics
of data
repository

Feedback &
Data Quality

**OHDSI cohort
studies & RCTs**

**OMOP
CDM**

Health neighbourhood

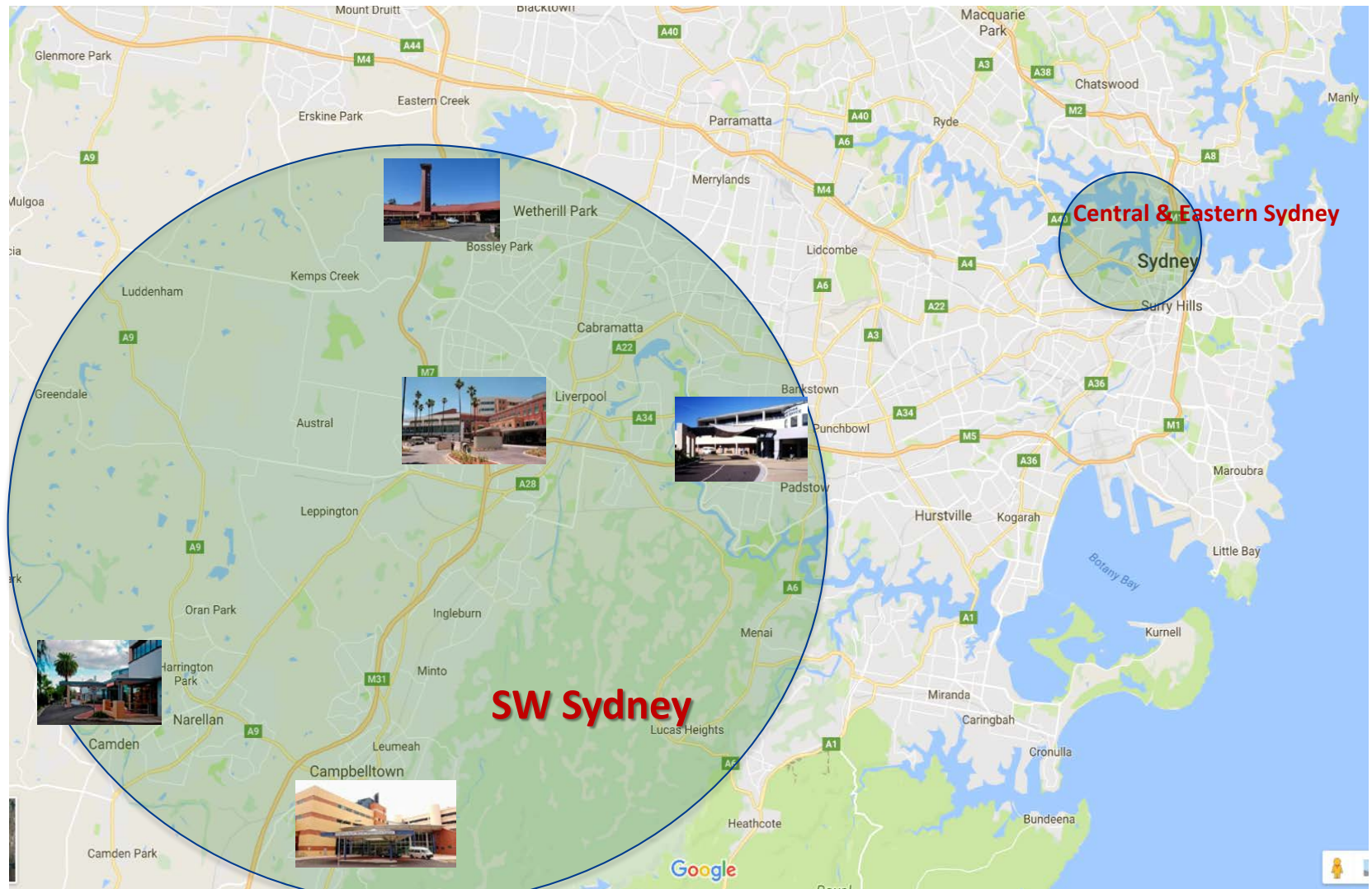
**ED, CHCs &
Outpatient
Clinics**

**Hospital
admissions**

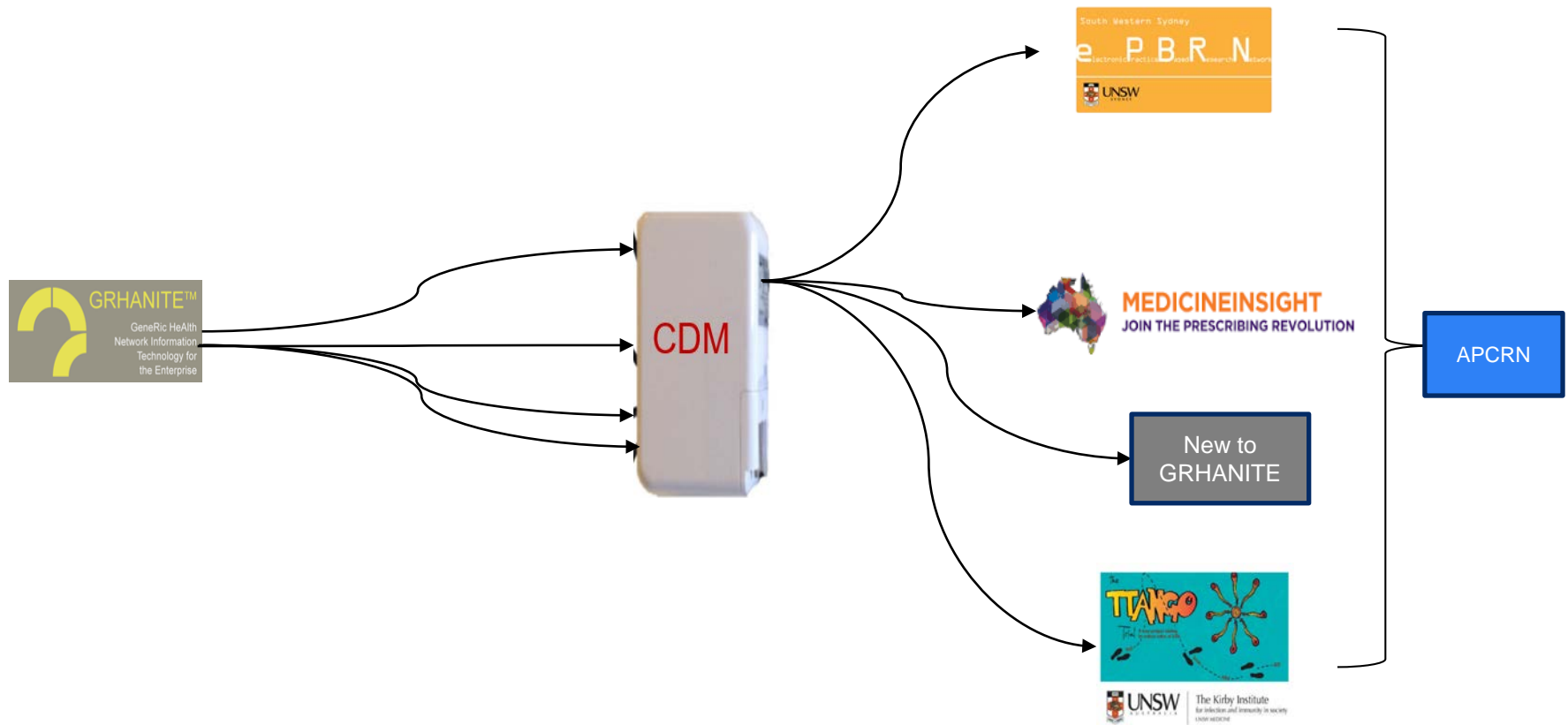


**UNSW
SYDNEY**

FUTURE: Sydney ePBRN & MedicineInsight



Future CDM work



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- Mr. Junior Borelli

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 - Mike Wu (cycle 1-5)
 - Su Lynn Yeoh (cycle 5)
 - Elizabeth Qian (cycle 5)
 - Ning Zhang(cycle 5)
- University of Melbourne
 - NPS Medicinewise
 - South Western Sydney PHN
 - South Western Sydney LHD

Collaborators



QUESTIONS

